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From Social to Sale: The Effects of Firm-Generated Content in Social Media on Customer Behavior

Given the unprecedented reach of social media, firms are increasingly relying on it as a channel for marketing communication. The objective of this study is to examine the effect of firm-generated content (FGC) in social media on three key customer metrics: spending, cross-buying, and customer profitability. The authors further investigate the synergistic effects of FGC with television advertising and e-mail communication. To accomplish their objectives, the authors assemble a novel data set comprising customers' social media participation data, transaction data, and attitudinal data obtained through surveys. The results indicate that after the authors account for the effects of television advertising and e-mail marketing, FGC has a positive and significant effect on customers' behavior. The authors show that FGC works synergistically with both television advertising and e-mail marketing and also find that the effect of FGC is greater for more experienced, tech-savvy, and social media–prone customers. They propose and examine the effect of three characteristics of FGC: valence, receptivity, and customer susceptibility. The authors find that whereas all three components of FGC have a positive impact, the effect of FGC receptivity is the largest. The study offers critical managerial insights regarding how to leverage social media for better returns.

Keywords: social media analytics, firm-generated content, digital marketing, customer relationship management, propensity score matching/difference-in-differences

Online Supplement: http://dx.doi.org/10.1509/jm.14.0249

With the dramatic change in the media landscape in recent years, firms have embraced social media as a means to engage with their customers. Recent business reports have suggested that total spending on social media advertising has increased worldwide ($17.74 billion in 2014 vs. $11.36 billion in 2013, which amounts to an increase of 56.2%) and that social media engagement drives sales (eMarketer 2015; Ogilvy & Mather 2011). However, the same studies have also suggested that more than 80% of marketers are concerned about measuring the returns on investment from social media. Recently, the popular social networking site Facebook implemented policy changes to filter out unpaid promotional material in users' news feeds that businesses post as status updates. This policy change makes it difficult for businesses to reach their Facebook "fans" with marketing content that is not paid for (Loten, Janofsky, and Albergotti 2014). Although this example illustrates the value of firm-initiated content on firms' social media pages, it also calls into question the added value of such postings beyond traditional media marketing (e.g., television advertisements) and/or other digital media marketing communication (e.g., e-mails).

In this study, we examine the effect of social media engagement on (individual-level) customer purchase behavior. More specifically, we study the effect of firm-generated content (FGC; i.e., firm-initiated marketing communication in its official social media pages) on two key customer metrics—customer spending and cross-buying behavior—that capture the transaction side and the relationship side, respectively, of the customer–firm relationship. We note that whereas customer spending is the "customer basket size"–based business performance metric on which firms typically focus, the degree of customer cross-buying captures the

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ISSN: 0022-2429 (print)
1547-7185 (electronic)

Journal of Marketing
Vol. 80 (January 2016), 7–25
DOI: 10.1509/jm.14.0249

breadth of a customer's relationship with a firm (Kumar, George, and Pancras 2008). Given the focus on customer profitability in the customer relationship management (CRM) literature (Kumar, Venkatesan, and Reinartz 2008), we also examine the effect of FGC on customer profitability.

Although firms are investing more in social media, marketing communications transmitted by television and e-mail are also important avenues by which firms can connect with their customers. From the perspective of integrated marketing communications (IMC; Naik and Raman 2003), it is vital to understand the relative efficacy and synergy between these media for marketing communications. Therefore, the first objective of this study is to examine the main effects of FGC and its synergistic effects with television advertising and e-mail marketing on customer spending and cross-buying.

In the social media era, the term "social CRM," in which firms engage in managing customer relationships through social media, is gaining prominence (Malthouse et al. 2013). For social CRM to be effective, it is crucial for a firm to understand how customers respond to FGC and whether certain segments of customers can benefit more from the firm's social engagement efforts. Thus, our second objective is to uncover how the effect of FGC varies across customer segments. We focus on the following customer characteristics that are relevant in our context: length of the customer–firm relationship, customers' technology savviness, and customers' propensity to use social networking sites regularly. These characteristics account for customers' motivation and ability to process information available through online channels such as e-mail and social media marketing communications.

To meet our objectives, we use microlevel customer behavior data compiled from multiple sources. We combine data on customers' participation in a focal retailer's social media page (which is hosted by a popular third party), individual customer-level in-store transaction/purchase data available both before and after the retailer's social media engagement efforts, and survey data on customer attitudes toward technology and social media. Leveraging this unique data set, we study the effect of customer engagement through social media on three customer metrics: spending, cross-buying, and customer profitability. To account for endogeneity concerns that could arise from (customer) self-selection and to establish the effect of FGC on customer behavior, we draw on recent studies in marketing (e.g., Huang et al. 2012) and employ the combination of propensity score matching (PSM) and difference-in-differences (DID) analysis. A recent business report (LoyaltyOne 2012) has suggested that although even short public statements on social media can spur transaction activity, more elaborate posts that elicit a higher level of customer participation can have a significant impact on a consumer's purchase behavior. We thus incorporate a rich formulation of FGC that captures three components: FGC valence/sentiment, FGC receptivity, and customers' susceptibility to FGC. Following recent literature (e.g., Das and Chen 2007; Tirunillai and Tellis 2012), we rely on the naive Bayes algorithm/classifier to categorize the valence or the sentiment of the postings: FGC receptivity takes into account customers' response to social media messages, and FGC susceptibility measures customers' predisposition toward using social media. This construction of FGC not only captures a firm's effort in creating meaningful content but also helps shed light on the role of customer response to FGC and the underlying mechanisms that may drive observed FGC effects.

Our results indicate that after we control for the main effects of television advertising and e-mail marketing and rule out the issue of customer self-selection, FGC has a positive and significant effect on customer spending and cross-buying behavior. Furthermore, we find that FGC works synergistically with both television advertising and e-mail marketing. We document that the synergistic effect of FGC and e-mail marketing is greater than the synergistic effect of FGC and television advertising. Our results also suggest that the effect of FGC is greater for more experienced, technologically savvy, and social network–prone customers. More importantly, we find that FGC is positively associated with customer profitability. By linking the effects of FGC and its interaction effects with television advertising (traditional media) and e-mail marketing (digital media) to customers' in-store purchase behavior, the results of this study contribute to research streams in IMC and multichannel marketing. From a practitioner's perspective, we quantify and compare the size effects of FGC with those of television advertising and e-mail marketing. By establishing the effect of FGC on customer profitability, we show that brand managers can use FGC not only for promoting products in social media but also for engaging with and nurturing profitable relationships with their customers.

Research Background

Studies in the area of social media have primarily focused on the effects of user-generated content (UGC) on market outcomes in various contexts such as book sales (Chevalier and Mayzlin 2006), movie box office revenues (Chintagunta, Gopinath, and Venkataraman 2010), and music album sales (Dhar and Chang 2009). Some studies have examined the motivations that underlie people's decisions to contribute content to social media (e.g., Toubia and Stephen 2013), while others have focused on how UGC interacts with traditional media marketing (Stephen and Galak 2012). Given that UGC serves as an effective source of word of mouth (Godes 2011) and an indicator of product quality (Tirunillai and Tellis 2014), the focus on the effects of UGC in previous research is understandable.

As firms increasingly rely on social media to engage with customers, recent studies have attempted to clarify different aspects of firms' engagement through social media. For example, Schulze, Schöler, and Skiera (2014) study the reach of viral marketing campaigns shared on social media and examine the effect of different types of sharing mechanisms (unsolicited messages, messages with incentives, direct messages from friends, and broadcast messages from strangers) on the reach of high-utility versus low-utility Facebook apps. Some studies have also examined how firms can harness the power of social media and the impact of social media marketing efforts on firms' return on investment (Kumar et al. 2013). With respect to the current research, one study that is relevant to ours is Danaher and Dagger (2013). The authors focus on the impact of a single promotional sale campaign that was advertised through ten types of media, including traditional and social media. They find that seven out of the ten media types influenced purchase outcomes, thus providing important insights into multimedia resource allocation.

In this study, we extend and contribute to this stream of literature by examining the effect of a firm's initiative to engage with its customers on social media (through FGC) over time. Because engagement over social media may take time to influence customer purchase behavior and could become more effective as the size of the social media community increases, studying social media communications and customer behavior over time can provide more meaningful insights. Unlike other media, firms' communications through social media platforms could be part of "equity"-building efforts that are particularly aimed at managing brands and nurturing customer relationships (Gensler et al. 2013). Therefore, although promotional sale campaigns such as the one analyzed in Danaher and Dagger (2013) help marketers understand the value of multimedia blitz campaigns, our focus on FGC includes both promotional and nonpromotional messages that go beyond generating short-term sales to help strengthen the bond between customers and firms.

Firm-generated content is essentially a multifaceted construct, and its effect depends on the message sentiment, customers' response to the message, and customers' innate disposition toward social media. We take into account these three factors and construct a composite measure that comprises FGC valence, receptivity, and customer susceptibility (we further explain these dimensions in the "Methods" section). This enables us to advance the understanding of how FGC works in creating and sustaining firms' long-term relationship-building efforts and helps differentiate our study from other studies engaged in examining the effect of social media communications. Like Danaher and Dagger (2013), we assess social media's return on investment by linking the effect of FGC to customer profitability. Finally, we make a concerted effort to account for customer heterogeneity and rule out inherent self-selection issues to establish the link between FGC and customer behavior, thus making new and significant contributions to this nascent research stream.

Conceptual Framework

In this section, we develop and present a conceptual framework (see Figure 1) that helps explain the effect of FGC on customer purchase behavior. Before we do so, we first describe our key dependent variables.

Customer Behavior: Spending Versus Cross-Buying

In this study, we focus on understanding the effect of FGC on two customer behaviors—customer spending and customer cross-buying—that help us examine the transaction side and the relationship side of the customer–firm relationship, respectively. Customer spending (in total dollars) captures the transactional value of the customer to the firm. By focusing on customer spending, we are able to capture how FGC influences a firm's top line as well as benchmark the effectiveness of FGC relative to television advertising and e-mail marketing. However, from a long-term perspective, a customer's cross-buying behavior, expressed in terms of the number of different product categories that a customer purchases, signals the intensity of the relationship between the customer and the firm (Shah et al. 2012; Verhoef and Donkers 2005). Firms often attempt to sell additional products and/or services to customers to engender greater customer loyalty. Firms use this cross-selling approach because customers who buy across several categories have greater switching costs, have a longer relationship with the firm, and contribute more toward firms' revenues and profits (Kumar, Venkatesan, and Reinartz 2008; Li, Sun, and Wilcox 2005). In our context, linking FGC to both the breadth and the intensity of the customer–firm relationship will help us better understand the role of FGC and will enable us to measure the returns of investing in social media. Although our primary focus is on customer spending and cross-buying behavior, we also supplement our core findings by examining the impact of FGC on customer profitability.[1]

FGC

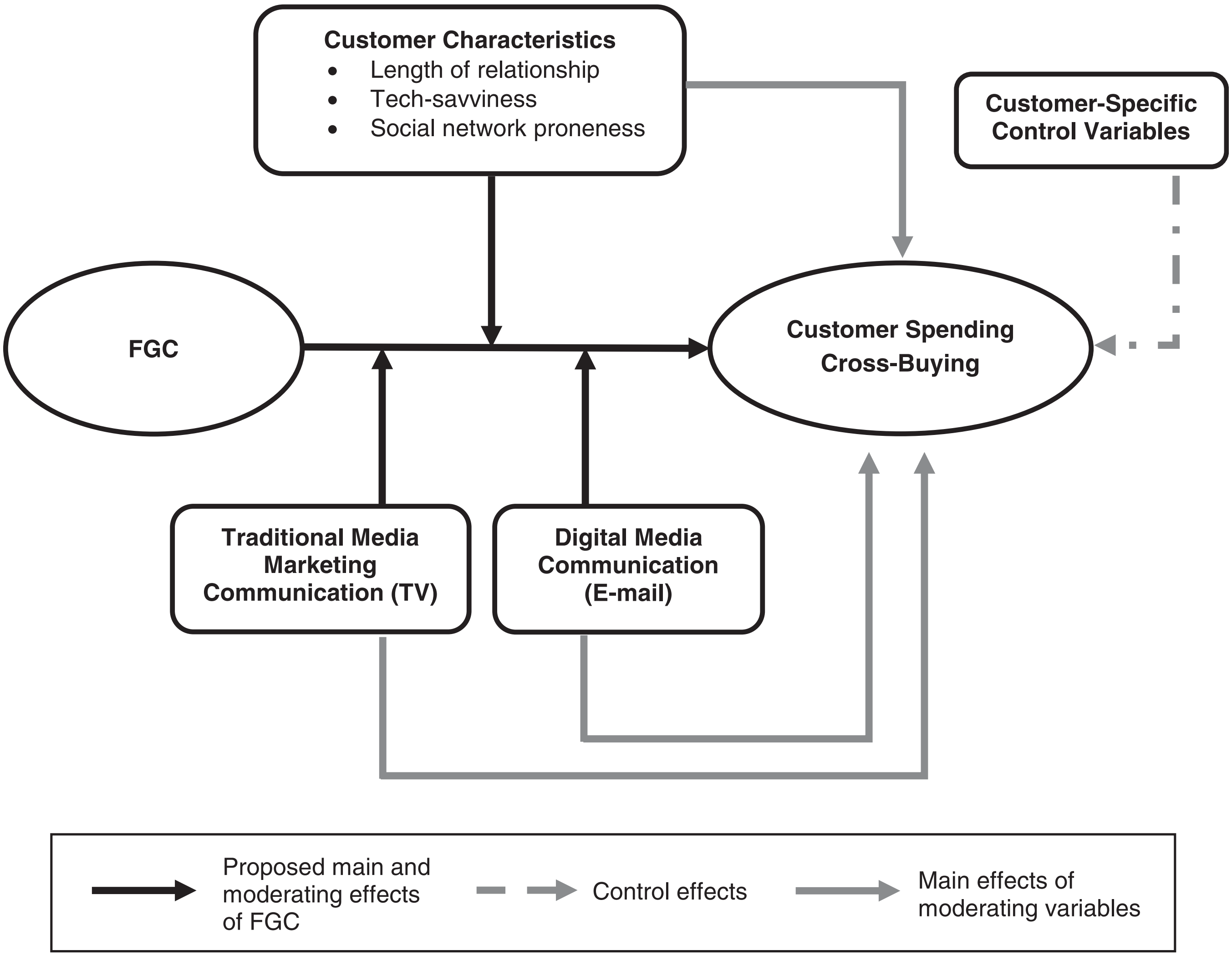
We refer to the messages posted by firms on their official social media pages as FGC and argue that FGC can help firms develop one-on-one relationships with their customers through social media's interactive nature. A recent business report (Lea 2012) has suggested that unlike in traditional media, the interaction between customers and firms over social media is mutually beneficial. We argue that FGC will positively affect customer behavior for the following reasons. First, similar to the role of traditional advertising in informing consumers and driving sales (Vakratsas and Ambler 1999), FGC can help firms tell customers about their current product offerings, prices, and promotions. Second, interactions with and virtual presence of other brand aficionados or fans can help in reinforcing favorable brand attitudes. Naylor, Lamberton, and West (2012) refer to "mere virtual presence" as the passive exposure to a brand's supporters in social media and argue that the inferred commonality between a focal user and other users in a social media community can create positive brand evaluations. Finally, when firms post content in social media, customers can respond by "liking" or commenting on the content, which can generate more positive brand evaluations.

Interaction of FGC with Television Advertising and E-Mail Marketing

Research in the area of IMC has emphasized the complex role of interactions between multiple media on the link between marketing and sales (Smith, Gopalakrishna, and Chatterjee 2006). In a recent study, Li and Kannan (2014) argue that there may be spillovers across multiple customer–firm touch points that should be accounted for when measuring cross-channel campaign effectiveness. Although television advertising and social media marketing differ in several aspects, they both serve as critical communication stimuli and can influence desired outcomes such as brand awareness in a similar way by

[1]Note that although our conceptual framework is very general, we use customers' in-store channel transaction data to measure their purchase behavior because that channel is the dominant channel for the retailer that we study.

FIGURE 1
Conceptual Framework



reinforcing each other (Bruhn, Schoenmueller, and Schäfer 2012). Firm-generated content can help increase the effectiveness of television advertising by providing appropriate links to products. Television advertising also often provides links to social media (e.g., a "Follow us on Facebook" message in a television ad for a product), thus integrating the two channels.

Similar to traditional advertising, e-mail messages may also work in tandem with social media. E-mail messages provide easy access to a firm's products and can be customized to increase customer response rates. E-mail marketing is known to be an effective and efficient way to reach a customer base (Ansari and Mela 2003). Thus, in our context, we examine the potential positive spillovers and synergies that may exist between FGC and traditional and e-mail marketing messages.

Interaction Effects of FGC with Customer Characteristics

For social media strategies to be effective, it is important for firms to understand whether the effect of social media engagement varies across different types of customers. We focus on the following three individual characteristics that can affect customers' motivation and ability to process information: length of relationship with a firm, technological skill level, and social network proneness.

Length of relationship. Studies in the branding area have suggested that brand familiarity is an important component of brand equity (Aaker 1991) and that marketing messages for familiar (vs. unfamiliar) brands evoke greater and more positive attitudinal responses from consumers (Campbell and Keller 2003). Research has also indicated that customers who have a longer relationship with a firm also have greater levels of satisfaction with it (Palmatier et al. 2006). Satisfied customers in turn may feel a higher level of commitment toward the firm (Ranaweera and Prabhu 2003) and thus be more likely to exhibit a favorable response to FGC.

Tech savviness. Firms are constantly introducing new technologies to appeal to tech-savvy customers. For example, Macy's recently introduced an app that enables its tech-savvy customers to shop from catalogs, billboards, and magazine ads (Gomez 2013). Tech-savvy customers are accessible through multiple digital touch points, and as retailers and brands engage with such customers through FGC, we expect tech-savvy customers to reciprocate by engaging more interactively with firms through their social media platforms. Tech-savvy customers are also more likely to supplement information they receive from FGC with other online sources (Schivinski and Dabrowski 2014) and derive greater benefits from social media engagement, thus leading to a greater response to FGC.

Social network proneness. In the digitally connected world, consumers are spending increasing amounts of time online interacting with other consumers with whom they may share common interests and consumption experiences. We refer to such consumers as "social network–prone" consumers. Mere virtual presence of a brand's supporters in social media can positively influence a focal consumer's purchasing behavior (Naylor, Lamberton, and West 2012). We argue that social network–prone consumers will place a greater value on the ability to connect with a firm's other customers to share their consumption experiences and thus will be more receptive to social media engagement. Furthermore, customers who use social media regularly will place more weight on the opinions of people with similar views (Schulze, Schöler, and Skiera 2014) and thus will likely exhibit a greater response to FGC and messages by other customers in the social media community.

Methods

Research Setting and Data

The data set for this study comes from a large specialty retailer that sells wine and spirits. The retailer operates multiple stores in the northeastern United States and manages an extensive loyalty card program through which it tracks customers' transactions at the individual product level. The retailer relies on both traditional media (e.g., television advertising) and e-mails to convey information about its offerings to its customer base.[2] The retailer began its foray into social media in August 2009 by creating a social media page and posting content on a popular social media networking site. It subsequently encouraged customers to sign up to become fans of and interact with the page. The social media site is not owned by the firm but is instead operated by a third party and is a popular social networking site.[3] The firm conducted a marketing campaign over television and e-mail informing customers about the presence of its social media page. No incentives (either monetary or promotional [e.g., coupons]) were offered, and customers signed up and participated of their own volition. After a customer participates in the firm's social media site (e.g., by clicking on the "like" button on the firm's social media page), FGC appears on the participating customer's social media page.[4] These "participating" customers may also receive e-mail messages about FGC when the firm posts them on its social media page. To that end, FGC is more readily available to participating customers and, thus, more likely to have an effect on the behavior of participating (vs. nonparticipating) customers. We note that the focal firm posts both promotional and nonpromotional content on its social media page. In the Appendix, we provide a few examples of FGC from the focal firm's social media page that illustrate that the firm uses social media for both promotional and nonpromotional marketing communication.

We gathered detailed information on the customers who participated in the focal firm's social media site (for details, see Web Appendix W1) and merged this social media participation data set with the customer transaction data set. For the purpose of our empirical analyses, we work solely with customers' in-store purchases because the majority of the retailer's sales occur in its physical stores. This process of merging customers' social media participation with (in-store) transaction data involves multiple steps, so we did this carefully, in conjunction with the cooperation of the focal firm. An important aspect of our data set is that we can also identify customers who do not take part in the focal firm's social media site (i.e., nonparticipants), and we have information on their purchases as well.

We also conducted a survey (in February 2011) of the same set of customers who participated in the firm's social media page. This survey was also sent to a subset of nonparticipant customers (i.e., those who did not participate in the focal firm's social media site). Consequently, we have attitudinal information obtained through surveys for customers who participated in the firm's social media as well as those who did not participate. We merged the survey data with customers' social media participation data and their in-store transaction data (customer in-store purchases) to create a comprehensive data set that we subsequently employ for our empirical analysis.

Model Development

Before we present the econometric model to establish the effect of FGC on customer spending and cross-buying behavior, we discuss some pertinent issues that need to be taken into account. Customers who have a greater affinity for the retail firm may be more likely to have a better transactional relationship with the firm (i.e., exhibit higher levels of spending and cross-buying) and also be more responsive to FGC by participating in the firm's social media page. In other words, customer-intrinsic variables (beyond the ones we control for) may simultaneously influence customers' purchase behavior and their responsiveness toward FGC. Thus, we must account for this plausible endogeneity/self-selection and rule out the reverse-causality issue to establish the effect of FGC on customer spending and cross-buying.

[2]The content used by the firm across the different media (i.e., social media, television, and e-mail) is usually distinct.

[3]For confidentiality reasons, we cannot disclose the name of the social media platform.

[4]Although customers can subsequently "unlike" the firm's page, we do not find such instances in our data set.

PSM. To account for the self-selection issue, we use the PSM technique to create two groups of customers: participant customers ("treatment" group customers)—those who choose to receive FGC by participating in the firm's social media—and nonparticipant customers ("control" group customers)—those who choose not to receive FGC and do not participate in the firm's social media. These two customer groups resemble each other before the firm's foray into social media, which creates a statistical equivalence between the two groups (Rosenbaum and Rubin 1985). After employing the PSM technique to create the two groups of customers, we use the DID modeling framework to examine the behavior of the two groups before and after the firm's venture into social media (pre-FGC and post-FGC time periods, respectively). In other words, by comparing the difference in behavior between the treatment and the control group customers before and after the firm's social media engagement (through FGC), we can estimate the impact of FGC.

Following prior literature (e.g., Girma and Görg 2007; Huang et al. 2012), we perform the matching procedure using data from the pre-FGC time period. We model customers' (binary) decision whether to participate in the firm's social media (and, thus, to receive FGC) using a logistic regression model of customer-specific explanatory variables (for details, see Web Appendix W2). We obtain the propensity scores to (pair-)match the control group customers who resemble the treatment group customers on the basis of propensity score similarity, using the 1:1 nearest-neighbor matching technique (Rosenbaum and Rubin 1985). As prior research has noted, this enables us to avoid bias that may occur when linking multiple, potentially dissimilar treatment and control group customers (Huang et al. 2012; Smith 1997).

We perform several checks to assess the validity of the PSM method (see Web Appendix W2). We do a visual analysis of propensity score distributions through box plots and histograms to ensure that there is a common support between the treatment and the control groups (Guo and Fraser 2010). We also perform the Kolmogorov–Smirnov test to verify that the propensity distributions of the two groups of customers are similar and conduct a sensitivity analysis to check for the presence of any hidden bias in the matching process. We also check whether the logistic regression model used for matching is able to correctly predict "group membership." We find that the model is able to predict treatment versus control group membership accurately for more than 93% of the customers. Having created a matched pair of treatment and control group customers using the PSM technique, we proceed to perform our DID analysis.

DID model. For the DID analysis, we selected the treatment group customers using a multistep process (for details, see Web Appendix W1) that yielded 412 customers. We used the PSM method outlined in the previous subsection to create a matched control group that has the same number of customers as the treatment group. For the DID model, we work with data from 85 weeks before and after the inception of the focal firm's social media page in August 2009. The pre-FGC period spans from January 2008 to July 2009 for all customers. The post-FGC period spans from August 2009 to March 2011 for the control group customers. Because the treatment group customers joined the social media page at different points in time (see Figure 2), the post-FGC period becomes effective for a customer only after he or she joins the firm's social media page. Our analysis is at the weekly level, which corresponds to a total of 170 weeks.

We conduct the DID analysis utilizing techniques expounded in the current literature (e.g., Bollinger, Leslie, and Sorensen 2011; Huang et al. 2012). For each matched pair (denoted by i), we model a focal customer's (denoted by h) spending and cross-buying behavior at time t (week) as follows[5]:

$$
\begin{aligned}
(1)\quad \text{Spend}^*_{iht} = {} & \alpha_{0ih} + \alpha_1\text{TCust}_{ih} + \alpha_2\text{FGC}_{iht} + \text{TCust}_{ih}\\
& \times \text{FGC}_{iht}(\alpha_3 + \alpha_4\text{TVAd}_{iht} + \alpha_5\text{Email}_{iht}\\
& + \alpha_6\text{CExp}_{iht} + \alpha_7\text{TechS}_{ih} + \alpha_8\text{SocialNet}_{ih})\\
& + \alpha_9\text{TVAd}_{iht} + \alpha_{10}\text{Email}_{iht} + \alpha_{11}\text{CExp}_{iht}\\
& + \alpha_{12}\text{TechS}_{ih} + \alpha_{13}\text{SocialNet}_{ih} + \alpha_{14}\text{PromD}_{iht}\\
& + \alpha_{15}\text{Dist}_{ih} + \varepsilon_{1iht}, \text{ and}
\end{aligned}
$$

$$
\begin{aligned}
(2)\quad \text{CrossBuy}^*_{iht} = {} & \beta_{0ih} + \beta_1\text{TCust}_{ih} + \beta_2\text{FGC}_{iht} + \text{TCust}_{ih}\\
& \times \text{FGC}_{iht}(\beta_3 + \beta_4\text{TVAd}_{iht} + \beta_5\text{Email}_{iht}\\
& + \beta_6\text{CExp}_{iht} + \beta_7\text{TechS}_{ih} + \beta_8\text{SocialNet}_{ih})\\
& + \beta_9\text{TVAd}_{iht} + \beta_{10}\text{Email}_{iht} + \beta_{11}\text{CExp}_{iht}\\
& + \beta_{12}\text{TechS}_{ih} + \beta_{13}\text{SocialNet}_{ih} + \beta_{14}\text{CrossP}_{iht}\\
& + \beta_{15}\text{Dist}_{ih} + \varepsilon_{2iht}.
\end{aligned}
$$

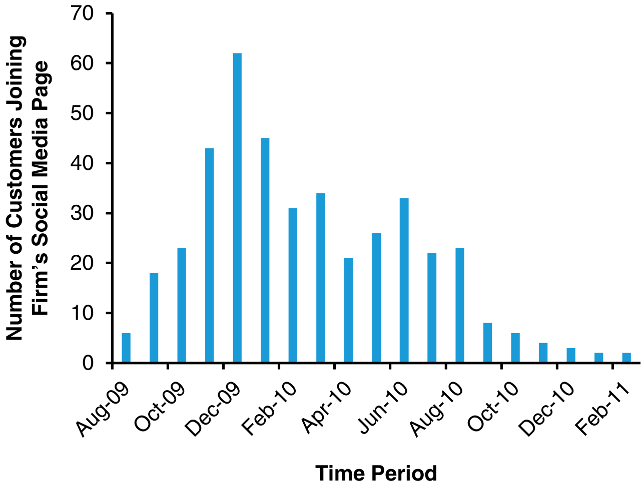
In Equations 1 and 2, Spend^*_{iht} and CrossBuy^*_{iht} refer to a customer h's (in the matched pair i) in-store spending and cross-buying, respectively, at time t. TCust_{ih} is a dummy variable that takes a value of 1 if customer h belongs to the treatment group, and 0 otherwise. FGC_{iht} is a dummy variable that is equal to 1 if a customer h is a recipient of FGC at time t, and 0 otherwise.[6] TVAd_{iht} and Email_{iht} refer to a customer h's exposure to television advertising and e-mail messages, respectively, at time t.[7] CExp_{iht}, TechS_{ih}, and SocialNet_{ih} denote customer h's length of experience with the firm, technological savviness, and social network proneness, respectively. The rest of the independent variables serve as customer-specific control variables. These include promotion depth index (PromD) and cross-category promotion (CrossP), which proxy for the customer's propensity to buy products on promotion, and distance of customers' residence from the store at which they shopped (Dist). We explain the operationalization of all these variables in the next subsection (see also Table 1). Note that we measure TechS and SocialNet using survey data (for the constructs, see Web Appendix W3). The error

[5]We note that we include all lower-order two-way interaction effects in the DID model. We find that our results are robust to the inclusion of all lower-order interaction effects. For the sake of brevity, we report only the relevant coefficients.

[6]$\text{FGC}_{iht} = 1$ for a treatment group customer only after a focal customer chooses to participate in the firm's social media page.

[7]For the DID model, television advertising and e-mail messages are coded as high (1) and low (0) levels on the basis of the median split across the panel of customers.

FIGURE 2
Histogram of Treatment Customers Joining the Firm's Social Media Page



terms ε_{1iht} and ε_{2iht} are associated with Equations 1 and 2, respectively. Because the error terms may be serially correlated, we follow Chib and Greenberg (1995) and specify the following structure:

$$(3)\qquad \begin{bmatrix} \varepsilon_{1iht} \\ \varepsilon_{2iht} \end{bmatrix} = \begin{bmatrix} \rho_1 \varepsilon_{1iht-1} + \upsilon_{1t} \\ \rho_2 \varepsilon_{2iht-1} + \upsilon_{2t} \end{bmatrix} 0 \le \left| \rho_{j=1,2} \right| < 1.$$

The residual error terms $[\Psi = (\upsilon_{1t}, \upsilon_{2t})]$ are distributed as $\Psi \sim N(0, \sigma^2 I)$. In Equations 1 and 2, because the values of Spend^*_{iht} and CrossBuy^*_{iht} may be 0 for some weeks, we use a Type I Tobit model as follows:

$$\text{Spend}_{iht} = \begin{cases} 0 & \text{if } \text{Spend}^*_{iht} \le 0, \quad \text{and} \\ \text{Spend}^*_{iht} & \text{otherwise} \end{cases}$$

$$\text{CrossBuy}_{iht} = \begin{cases} 0 & \text{if } \text{CrossBuy}^*_{iht} \le 0 \quad . \\ \text{CrossBuy}^*_{iht} & \text{otherwise} \end{cases}$$

To account for heterogeneity in customers' response behavior, we use a hierarchical Bayesian framework (e.g., Rossi, Allenby, and McCulloch 2006) as follows:

$$(4)\qquad \Lambda_h = \Theta_0 + \Theta_1 G_h + \Phi_h,$$

where Λ_h is the vector comprising $[\alpha_{0ih}, \beta_{0ih}]'$, and G_h and Θ_1 are the matrix of customer demographic variables representing age, gender, and race (Table 1) and the matrix of these variables' corresponding coefficients, respectively. In the term $\Phi_h \sim \text{MVN}(0, K)$, K denotes the variance–covariance matrix.

In Equations 1 and 2, as mentioned previously, we follow prior literature (e.g., Angrist and Pischke 2009) in defining the main variables TCust_{ih} and FGC_{iht} as dummy variables. This enables us to interpret the relevant parameters as causal effects. We note that the causal interpretation is valid under the assumption that except for social media participation, the treatment and the control groups are similar (within the bounds of PSM that we employ). However, the operationalization of FGC as a categorical variable does not allow us to capture the various dimensions of FGC, such as valence and response from customers (we discuss these salient dimensions of FGC in the next subsection). Thus, we first utilize the DID model to establish the causal impact of FGC (within the bounds of PSM) and subsequently use another model specification—a variation of the treatment effects (TE) model—to capture the richness of the FGC construct.

TE model. The TE model accounts for endogeneity issues (e.g., from self-selection) by explicitly considering the endogenous variable and incorporating it into the modeling framework. A typical TE model setup consists of two components: (1) a selection equation that models the endogenous variable through which customers might self-select (in our case, the endogenous variable is customers' self-selection through their participation in the firm's social media page and subsequent access to FGC) and (2) given the self-selection variable, a set of outcome equations to model the phenomenon of interest (in our case, customer spending and cross-buying). Next, we describe the outcome equations of our proposed TE model:

$$\begin{aligned}(5)\qquad \text{Spend}^*_{iht} = {} & \gamma_{0ih} + \text{FGC}_{iht}(\gamma_1 + \gamma_2 \text{TVAd}_{iht} + \gamma_3 \text{Email}_{iht} \\ & + \gamma_4 \text{CExp}_{iht} + \gamma_5 \text{TechS}_{ih} + \gamma_6 \text{SocialNet}_{ih}) \\ & + \gamma_7 \text{TVAd}_{iht} + \gamma_8 \text{Email}_{iht} + \gamma_9 \text{CExp}_{iht} \\ & + \gamma_{10} \text{TechS}_{ih} + \gamma_{11} \text{SocialNet}_{ih} + \gamma_{12} \text{PromD}_{iht} \\ & + \gamma_{13} \text{Dist}_{ih} + \varepsilon_{3iht}, \text{ and}\end{aligned}$$

$$\begin{aligned}(6)\qquad \text{CrossBuy}^*_{iht} = {} & \delta_{0ih} + \text{FGC}_{iht}(\delta_1 + \delta_2 \text{TVAd}_{iht} + \delta_3 \text{Email}_{iht} \\ & + \delta_4 \text{CExp}_{iht} + \delta_5 \text{TechS}_{ih} + \delta_6 \text{SociaNet}_{ih}) \\ & + \delta_7 \text{TVAd}_{iht} + \delta_8 \text{Email}_{iht} + \delta_9 \text{CExp}_{iht} \\ & + \delta_{10} \text{TechS}_{ih} + \delta_{11} \text{SocialNet}_{ih} + \delta_{12} \text{CrossP}_{iht} \\ & + \delta_{13} \text{Dist}_{ih} + \varepsilon_{4iht}.\end{aligned}$$

We model the selection equation (the endogenous variable by which customers self-select) in a probit framework as follows:

$$\begin{aligned}(7)\qquad \text{CustPar}^*_{iht} = {} & \varphi_{0ih} + \varphi_1 \text{PrivCon}_{ih} + \varphi_2 \text{IMov}_{ih} \\ & + \varphi_3 \text{TechS}_{ih} + \varphi_4 \text{SMov}_{ih} + \varphi_5 \text{OEnt}_{ih} \\ & + \varphi_6 \text{TimeOnSocialNet}_{ih} + \varepsilon_{5iht},\end{aligned}$$

where i indexes the matched pair of treatment or control group customers, h indexes customer, and t indexes time period. In Equation 7, CustPar^*_{iht} is the latent utility that a customer h derives by participating in the firm's social media site at time t and thereby choosing to receive FGC. We model a focal customer's propensity to participate in the firm's social media as a function of the customer's attitudes toward online privacy concerns (PrivCon), motivation to use the Internet to search for information (IMov), technology savviness (TechS), motivation to socialize online (SMov), proclivity to use the Internet for online entertainment (OEnt), and time spent on online social networking sites per day (TimeOnSocialNet). We provide details regarding the measurement of these constructs in

TABLE 1
Variable Operationalization and Summary Statistics

Variable Description	Variable Notation	Variable Operationalization	Mean	SD
Social Media Participation Data, Traditional (TV Ad), and Digital (E-mail) Marketing Communications Data				
Firm-generated content	FGC	Messages posted by the firm (# of postings/week; see Equation 8 and Web Appendix W8)	3.78	1.82
Customer participation	CustPar	Equal to 1 if customer h participates in firm's social media page at time t, and 0 otherwise		
Television advertising	TVAd	Television ad score based on GRPs per week	40.79	26.42
E-mail advertising	Email	Total number of e-mails sent by the firm that are opened by customer h during week t (# of e-mails opened/week/customer)	1.63	1.02
Customer Transaction Data				
Spending behavior	Spend	Total dollar amount spent by customer h during week t on firm's products ($/week/customer)	14.34	7.26
Cross-buying behavior	CrossBuy	Total number of distinct categories customer h purchased during week t (# of distinct categories bought/week/customer; see Web Appendix W7)	3.23	1.24
Customer experience	CExp	Duration of the relationship of customer h with the firm until week t (# of weeks of relationship with focal firm/customer)	94.26	17.89
Promotion depth index	PromD	Weighted average of price cuts availed by customer h for week t across all product items purchased (cents/ml/week)	.38	.65
Cross-category promotion	CrossP	Proportion of categories bought on promotion by customer h for week t (proportion of categories bought on promotion/week/customer)	.46	.21
Survey Data				
Time spent on social network	TimeOnSocialNet	Time spent on social networks (from survey; minutes/customer)	41.54	8.50
Online social profile	OProf	Number of online social profiles (# online social profiles/customer)	2.47	1.15
Age	Age	Age of customer h (years/customer)	45.46	18.52
Distance	Dist	Distance between customer h and the focal store (miles/customer)	5.17	8.06
Attitudinal variables	TechS		3.69	.80
	SocialNet		2.77	1.22
	PrivCon	These constructs are measured by survey (for	1.55	.51
	IMov	measurement details, see Web Appendices W3	4.08	.65
	SMov	and W4)	2.88	.76
	EscMov		2.12	.80
	OEnt		2.77	.78
Gender	Gender	Equal to 1 if customer h is male, and 0 otherwise	47%	
Race	Race	Equal to 1 if customer h is white, and 0 otherwise	86%	

Notes: Summary statistics for customer transaction data are unconditional on purchase occasions. The summary statistics are based on a matched pair of 412 customers from each of the treatment and the control groups.

the Web Appendix (for the constructs and the reasoning for including these variables, see Web Appendices W4 and W5, respectively). Note that because we estimate the TE model on the matched sample, we do not use these variables for matching. Furthermore, whereas these Internet-, technology-, and social media–related variables are likely to affect customers' decisions whether to participate in social media, they are not likely to affect customers' in-store behavior. This helps us rule out reverse causality. We link the latent utility of customer participation to their observed social media participation (and, thus, their received FGC) as follows. Let CustPar_{iht} denote a binary variable that takes on the value 1 if the focal customer h (of the matched pair i) participates in the firm's social media site at time t, and 0 otherwise. Then, we have the following:

$$\text{CustPar}_{iht} = \begin{cases} 1 & \text{if } \text{CustPar}^*_{iht} > 0 \\ 0 & \text{otherwise} \end{cases}.$$

We draw readers' attention to a few points with respect to the sample, the formulation, and the estimation of the TE model. First, we note that the TE model is relevant only after the firm began to engage with its customers through FGC (August 2009 onward). We thus use data only from the post-FGC period (which spans 85 weeks from August 2009 to

March 2011). We select treatment group customers using the same multistep process as mentioned previously (for details, see Web Appendix W1), and we select the control group customers using the same PSM technique as outlined previously. However, for the TE model, we end up with slightly fewer (394) treatment customers because of the restrictions imposed.[8] Thus, our sample for the TE model consists of 394 customers each from the treatment and the control groups (i.e., a total of 788 customers). Second, unlike for the DID model, for the TE model, FGC, television advertising, and e-mail messages are continuous variables (though, for the sake of convenience, we use the same notation as that used for the DID model). As with the DID model, we estimate Equations 5, 6, and 7 jointly. Likewise, we also account for heterogeneity and cast the TE model in a hierarchical Bayesian framework.

For both the DID and the TE models, given that we are estimating the outcome variables (Equations 1–2 and 5–7) simultaneously, we use exclusion restrictions to aid in the econometric identification of the model parameters. We exclude promotion depth (PromD) and cross-category promotion (CrossP) from the cross-buying and spending equations, respectively. Our arguments are as follows. Promotion depth represents the extent or the amount of savings the customer realizes from buying the products that are on sale. We expect that customers who realize these higher savings will spend more because of their (increased) planned and/or unplanned purchases of other products (Stilley, Inman, and Wakefield 2010). However, there is no reason to believe that they would buy more from different product categories. In a similar vein, the more categories that are on promotion, the greater the likelihood that a customer will buy from multiple categories, which positively affects his or her cross-buying. Thus, we expect cross-category promotion (CrossP) to be more strongly correlated with the cross-buying variable. In the "Robustness Checks" subsection, we empirically test for the validity of the set of exclusion restrictions.

We estimate our models using hierarchical Bayesian methods with Markov chain Monte Carlo techniques. We use a total of 50,000 iterations with a "burn-in" of 40,000 iterations. After ensuring that the convergence criteria are met, we use the last 10,000 iterations for calculating posterior means and standard errors of the model parameters (for details, see Web Appendix W6).

Variable Operationalization

Spending and cross-buying. We measure focal customer h's spending (denoted by Spend) as the dollar amount spent on alcohol/liquor products in a given time period. Customer cross-buying behavior (CrossBuy) represents the breadth in customers' buying patterns and is operationalized as the number of distinct categories in which a customer purchases in a given time period t (Kumar, George, and Pancras 2008; Shah et al. 2012). In our context, to construct this variable, we first need to identify the relevant categories. We rely on reports from trade magazines, interviews with managers, and sales information derived from the transaction data to define the categories. This process led to the categorization of wines into red, white, and sparkling wines and spirits into whiskey, tequila, rum, vodka, and gin. Thus, we have a total of eight categories representing wine and spirits (for details, see Web Appendix W7).

FGC, television advertising, and e-mail messages. For the TE model, we operationalize FGC as the number of original messages posted by the firm that are accessible to a participating customer in a given time period. We give different weights to different postings on the basis of the three dimensions of FGC valence, FGC receptivity, and (customers') susceptibility to FGC. The valence of each post reflects the sentiment conveyed by that post (VPost). Following recent literature (e.g., Tirunillai and Tellis 2012; Das and Chen 2007), we rely on the naive Bayes algorithm/classifier to classify sentiment into three categories: positive, neutral, or negative (coded as 1, 0, and –1, respectively). Customers may respond to FGC by liking the post, commenting on the post, and/or sharing the post with their network. For each FGC posting, we sum the total comments, likes, and shares received by that posting to calculate the receptivity measure (RPost). Because customers may differ in their susceptibility to social media and FGC, we include this measure as an additional dimension of FGC. To operationalize susceptibility, we used the customer survey in which we queried customers with regard to their predisposition toward social media. We present the constructs related to the formulation of FGC susceptibility (FGCSuscept) in Web Appendix W8. Using these three dimensions, we formulate FGC (across N_t postings each denoted by k for each customer h and for time period t) as follows:

$$\text{(8)}\quad \text{FGC}_{ht} = \left[\left(\frac{\sum_{k=1}^{N_t}(\text{VPost}_{kt} \times \text{RPost}_{kt})}{N_t}\right) \times \text{FGCSuscept}_h\right].$$

We use this FGC formulation in Equations 5 and 6 for the treatment group customers from the matched pair (note that FGC will be 0 for the control group customers) upon participation. Note that we also investigate the efficacy of the individual components of the FGC defined previously.

We operationalize television advertisements (denoted by TVAd) at the customer-week level. Previous literature has documented that for memory decay and related reasons, past advertising may not be as effective as recent advertising. To accommodate this, following Tellis and Weiss (1995), we first adopt a stock formulation for television advertising (denoted by TVAdStock_t) as follows: $\text{TVAdStock}_t = \eta\text{GRPTVAd}_t + (1 - \eta)\text{TVAdStock}_{t-1}$, where $\eta \in (0, 1)$[9] is

[8]For the DID model, the restriction is that customers need to make at least one purchase each in the pre- and post-FGC periods; for the TE model, the restriction is that customers have to make at least two purchases in the post-FGC period. We impose these restrictions to reliably estimate the heterogeneity parameters.

[9]To reduce computational burden, we do not estimate η. Instead, we use a grid search procedure to obtain its optimum value. We find that $\eta = .8657$ provides the lowest log-marginal likelihood. More information is available on request. Note that although we use stock formulation to capture the phenomenon of interest more accurately, we caution that using the stock variable may complicate the interpretation of interaction parameters.

the decay parameter and $GRPTVAd_t$ refers to average gross rating points (GRPs) across all broadcast television advertisements at time t. To make this variable customer specific, we multiply it by the average number of hours of television watched weekly by the customer as follows: $TVAd_{ht} = TVAdStock_t \times W_h$, where W_h is the average weekly number of hours of television watched by the customer.[10] In our data set, we observe whether a customer h opened a specific e-mail sent by the focal retailer. We operationalize $E\text{-mail}_{ht}$ as the number of e-mails sent by the firm that a customer h opens in time period t.

Customer-specific variables. We capture customer experience (CExp) by the length (in weeks) from the date of the focal customer's first transaction with the retailer until time t. We utilize survey data to measure the attitudinal variables used in our empirical analysis (see Table 1). These include the two focal customer-specific variables in the conceptual framework (i.e., customers' technology savviness [TechS] and social network proneness [SocialNet]) and the explanatory variables to model customers' social media participation (see Equation 7). This set of variables includes customers' attitudes toward online privacy concerns (PrivCon), their motivation to use the Internet to search for information (IMov), their motivation to socialize online (SMov), their use of the Internet for online entertainment (OEnt), and their time spent on a social network per day (TimeOnSocialNet). We also use the focal customer's number of online social profiles and use of the Internet to escape reality as matching variables in PSM. We provide information related to the measurement of these constructs in Web Appendix W4. All the factor loadings are significant ($p < .01$), which suggests convergent validity. Cronbach's alphas for the constructs range from .73 to .89, which indicates good reliability.

Other control variables. With respect to the control variables, we calculate the promotion depth index variable (PromD) for each customer h at time t as the weighted average of all price discounts that customer used across all product items (across the eight categories) purchased. The weights are given by the volume share of each product item bought by the customer and are computed as constant weights (i.e., average share weights across the full sample period; Pauwels and Srinivasan 2004). Cross-category promotion (CrossP), which captures a focal customer's proneness to buy products on promotion across categories, is operationalized as the proportion of total categories bought on promotion by customer h at time period t (for details, see Web Appendix W9). The operationalization of customer demographic variables is straightforward, as is the distance variable (average distance in miles from customers' residence to the store at which they shop; see Table 1).

[10]We obtain this information from the customer survey. The average weekly number of hours of television watched for the treatment group customers is 22.38, and the corresponding number is 19.82 for the control group customers. This difference is not significant at the 5% level.

Customers in our sample, on average, spend \$14.34 per week (or \$49.80 per purchase visit). However, note that there are weeks during which customers do not make any purchases. On average, customers buy from 3.23 categories per store visit. This (relatively) high number is reflective of the product category we analyze (wine and liquor) because consumers tend to seek variety when purchasing these products. As Table 1 shows, there is significant heterogeneity across customers for both spending and cross-buying. The retailer posts approximately three to four messages in a typical week. The high level of television advertising indicates that the retailer uses the television medium regularly to communicate with its clientele. Customer response to the retailer's e-mail messages is quite high. On average, in a given week, a customer opens 1.63 e-mails sent by the retailer. With respect to customer characteristics, the average customer experience is 94.26 weeks. Customers travel an average distance of 5.17 miles to shop at the store. The average age of consumers in our sample is 45 years, and the minimum age is 23 years. For brevity, we summarize the operationalization of the variables and their descriptive statistics in Table 1.

Results

Model-Free Evidence

Before we report the results of the model, we present model-free evidence (see Table 2) using the average DID for the outcome variables. The "raw" numbers compare the outcome variables across the two groups of customers—the treatment and the control groups—and across the two time periods—the pre-FGC period and the post-FGC period. We perform these calculations at the weekly level to account for the different participation times of the treatment group customers. Although we find that there is no significant difference (at the 5% level) in weekly spending and cross-buying between the treatment and control group customers in the pre-FGC period (\$13.52 vs. \$13.35 and 3.08 vs. 2.95 for spending and cross-buying, respectively), a significant difference (at the 5% level) emerges in the post-FGC period across these customer groups (\$15.96 vs. \$14.53 and 3.74 vs. 3.15 for spending and cross-buying, respectively). Following Dagger and Danaher (2014), we find statistically significant and positive overall DID values (\$1.26 and .46 for spending and cross-buying, respectively), indicating the positive effect of FGC on customer behavior. These sets of results help rule out the issue of reverse causality and lend prima facie evidence to the (positive) effect of FGC on customer spending and cross-buying behavior. Next, we present the formal results of the DID and the TE models.

DID and TE Model Results

We present the results of the proposed DID model (Equations 1–4) along with its (several) alternative specifications in Table 3. We rely on log-marginal density

TABLE 2
Average DID: Purchase Behavior of the Treatment Group Versus the Control Group

Outcome Variable	Groups	Post-FGC	Pre-FGC	Difference	DID
Spending ($)	Treatment group	15.96	13.52	2.44** (.92)	1.26**
	Control group	14.53	13.35	1.18 (1.01)	
Cross-buying	Treatment group	3.74	3.08	.66** (.25)	.46**
	Control group	3.15	2.95	.20 (.19)	
Profit ($)	Treatment group	5.91	4.79	1.12** (.43)	1.02**
	Control group	4.78	4.68	.10 (.09)	

**$p \leq .01$.

Notes: Standard errors are shown in parentheses. The table presents the mean values of customer behaviors (spending, cross-buying, and customer profitability) at the weekly level. The pre-FGC and post-FGC periods comprise 85 weeks each for all the customers in the control group. Given that the treatment group customers can join the focal firm's social media page at different times, the number of weeks for the pre-FGC and post-FGC analyses varies across the treatment group customers. Whereas the "difference" measure is based on the paired-sample t-test, we determine the DID measure by calculating the difference in the outcome variables between post- and pre-FGC periods and then comparing the means of these differences between the treatment and control groups. These analyses are based on matched pairs of 412 customers from each of the treatment and the control groups.

(LMD) computed using the Newton–Raftery method (Rossi, Allenby, and McCulloch 2006, p. 168) to assess the fit of the models. The first model in Table 3 (M1) is the standard DID model reported in the literature and serves as a benchmark model. This model does not contain variables related to television advertising and e-mail marketing or control variables, nor does it incorporate the Type I Tobit specification or account for serial and cross-correlations. The subsequent models (M2–M5) build on the basic model sequentially by considering additional variables and model specifications. The "full" model (M5) includes the main effect of FGC, its interaction effects with television advertising and e-mail marketing, and control variables. Moreover, the full model also incorporates customer heterogeneity (using hierarchical Bayesian methods; see Equation 4), adopts a Type I Tobit specification, and accounts for serial and cross-correlations. Not surprisingly, this model has the best fit. The main parameters of interest are α_3 and β_3, which capture the effect of FGC on the spending and the cross-buying behavior, respectively, of participant customers relative to nonparticipant customers in the post-FGC (vs. pre-FGC) period. These parameters are positive and significant across all models, which attests to the positive effect of FGC on customer spending and cross-buying.

We present the results of the TE model in Table 4, Panels A and B. As for the DID analysis, we have the standard TE model (Model 1), which includes only the main effect of FGC. In Models 2–5, we sequentially enrich Model 1 by including additional variables and extending model specifications. The "full model" (Model 5) captures the main effect of FGC, along with its interactions with television advertising and e-mail marketing, and includes control variables and customer characteristics. This model also accounts for customer heterogeneity, Type I Tobit specification, serial correlations, and cross-correlations, and it offers the best fit. Because the full models have the best fit for both DID and TE models, we refer to them when discussing our results.

Our results suggest that FGC has a positive and significant effect on customer spending and cross-buying. This is true for the parameter estimates obtained from both the DID model (1.32 and .49 for spending and cross-buying, respectively) and the TE model (.18 and .11 for spending and cross-buying, respectively). The parameters associated with the interaction effects between FGC and television advertising (DID: .0057 and .0001; TE: .0621 and .0019 for spending and cross-buying, respectively) and the interaction effects between FGC and e-mail marketing (DID: .0991 and .0047; TE: .1755 and .1137 for spending and cross-buying, respectively) are positive for customer spending and cross-buying for both the models. These results suggest that there are synergistic effects between FGC and television advertising and between FGC and e-mail-based marketing communication.

Turning our attention to the interaction effects between FGC and customer characteristics, our results suggest that FGC has a greater effect on more experienced customers for both customer spending and cross-buying (DID: .1686 and .0797; TE: .0450 and .1228 for spending and cross-buying, respectively). We find that FGC has a greater effect on customers who are more tech savvy (DID: .2753 and .0303; TE: .0918 and .0281 for spending and cross-buying, respectively) and those who are more prone to using social media (DID: .1906 and .1523; TE: .1091 and .0956 for spending and cross-buying, respectively). Taken together, the results from the DID and the TE models are consistent.

With regard to other results, we find that, as we expected, both television advertising and e-mail marketing have a positive effect on customer spending and cross-buying. In Table 4, Panel B, we present the results related to customers' participation in the focal firm's social media site. We find that most of the results are in the expected direction. Customers with greater privacy concerns are less likely to participate in the firm's social media site. Likewise, customers who have a greater motivation to seek information, are more tech savvy, have a greater motivation to socialize online, and use the Internet for online entertainment are more likely to become part of the firm's social media site. We also find that customer social media participation, spending, and cross-buying are positively correlated.

TABLE 3
Results of the DID Model: Spending and Cross-Buying Behavior

	M1		M2		M3		M4		M5	
Variables	Spending	Cross-Buying	Spending	Cross-Buying	Spending	Cross-Buying	Spending	Cross-Buying	Spending	Cross-Buying
TCust	.1860	.1316	.1723	.1292	.1632	.1099	.1518	.1029	.0803	.0941
FGC	1.1639	.1898	1.064	.1878	1.0463	.1725	1.0166	.1558	.9851	.1291
TCust × FGC	1.2468**	.4582**	1.2766**	.4597**	1.3031**	.4693**	1.3093**	.4790**	1.3233**	.4987**
TCust × FGC × TVAd	—	—	—	—	.0085**	4.E-05**	.0026**	.0009**	.0057**	.0001**
TCust × FGC × Email	—	—	—	—	.0791**	.0020**	.0704**	.0026**	.0991**	.0047**
TCust × FGC × CExp	—	—	—	—	.1282**	.0777**	.1007**	.0788**	.1686**	.0797**
TCust × FGC × TechS	—	—	—	—	.1816**	.0090**	.1351**	.0097**	.2753**	.0303**
TCust × FGC × SocialNet	—	—	—	—	.1978**	.1370**	.0957**	.1161**	.1906**	.1523**
TVAd	—	—	.4285**	.2221**	.0737**	.1928**	.0260**	.1714**	.1373**	.1733**
Email	—	—	1.3489**	.2406**	1.1074**	.0157**	.9895**	.0215**	.9268**	.1242**
CExp	—	—	.5005**	.3206**	.6232**	.3001**	.5519**	.2897**	.7579**	.336**
TechS	—	—	–.6772**	–.0983**	–.4884**	–.2494**	–.4636**	–.2048**	–.5285**	–.2062**
SocialNet	—	—	–.3592**	–.0417**	–.8194**	–.3392**	–.7791**	–.3343**	–.5906**	–.3596**
PromoD	—	—	5.0113**	—	4.3664**	—	4.4414**	—	3.9708**	—
CrossP	—	—	—	1.1168**	—	1.1192**	—	1.0130**	—	.6949**
Dist	—	—	–.5020*	–.0628	–.4686*	–.0429	–.3949*	–.0259	–.3019*	–.0316
Gender	—	—	1.3071	.2368	1.1031	.2057	1.0071	.2310	.9660	.4133
Race	—	—	1.0456	.1251	.6228	.3838	.7753	.2758	.7214	.2093
Age	—	—	.0555	.1927	.1773	.2396	.1158	.2758	.2778	.3005
Intercept	13.2638**	3.1962**	12.3664**	3.5017**	11.0745*	3.2707*	11.9997*	3.1307**	6.2314*	2.6182**
Serial correlation	X	X	X	X	X	X	.0200*	.0509	.0187*	.0482
Cross-correlation	X		.5321**		.5134**		.5018**		.4765**	
Heterogeneity	X		✓		✓		✓		✓	
Number of observations	140,080		140,080		140,080		140,080		140,080	
Sample size	824		824		824		824		824	
LMD	–79,248.44		–73,270.09		–67,878.06		–66,366.26		–56,313.75	
Model description	Standard DID		M1 + Controls		M2 + Interaction		M3 + Serial correlation		M4 with Tobit	

*$p \leq .05$ (parameter is significant at the 95% level; i.e., the 95% confidence interval does not contain 0).
**$p \leq .01$ (parameter is significant at the 99% level; i.e., the 99% confidence interval does not contain 0).
Notes: The sample size of 824 customers is based on a matched pair of 412 customers from each of the treatment and the control groups.

Supplementary Analysis

Profitability Analysis

To assess the impact of FGC on the focal retailer's bottom line, we analyze the impact of FGC on customer profitability. Leveraging our access to data on both retailer prices and costs at the individual product level, we compute customer-specific aggregated net total profits per period accrued to the firm as a result of purchases made by our sample customers. We use this measure in our analysis in lieu of customer spending. Raw DID analysis (see Table 2) suggests that whereas there is no significant difference in customer profitability for the control group across the pre-FGC and the post-FGC periods, there is a significant difference (at the 5% level) in customer profitability for the treatment group customers before and after social media participation. The average DID value for customer profitability is \$1.02, which is statistically significant at the 5% level. This finding suggests that compared with nonparticipating customers, customers who participate in the focal firm's social media contribute \$1.02 more toward the focal firm's profits (in the post-FGC period relative to the pre-FGC period).

Next, to formalize the effect of FGC on customer profitability, we begin by reestimating the DID model presented in Equations 1–4. Given that our proposed DID model is a joint model (with cross-buying), we reestimate the model by replacing customer spending with customer profitability and leave the rest of the variables and the model specification unchanged. We find that FGC has a significant effect on customer profitability, with the other results being substantively similar to those found previously

TABLE 4
Results of the TE Model

A: Spending and Cross-Buying Behavior

Variables	Model 1 Spending	Model 1 Cross-Buying	Model 2 Spending	Model 2 Cross-Buying	Model 3 Spending	Model 3 Cross-Buying	Model 4 Spending	Model 4 Cross-Buying	Model 5 Spending	Model 5 Cross-Buying
FGC	.1153**	.0158**	.1240**	.0237**	.1394**	.0205**	.1384**	.0328**	.1835**	.1103**
FGC × TVAd	—	—	—	—	.0388**	.0019**	.0444**	.0012**	.0621**	.0019**
FGC × Email	—	—	—	—	.1653**	.0864**	.1546**	.0866**	.1755**	.1137**
FGC × CExp	—	—	—	—	.0104**	.0468**	.0206**	.0611**	.0450**	.1228**
FGC × TechS	—	—	—	—	.0799**	.0142**	.0736**	.0076**	.0918**	.0281**
FGC × SocialNet	—	—	—	—	.0780**	.0252**	.0697**	.0468**	.1091**	.0956**
TVAd	—	—	.0410**	.0332**	.0443**	.0450**	.0731**	.0615**	.1082**	.1218**
E-mail	—	—	.7943**	.1087**	.8627**	.1199**	.8832**	.1141**	1.0258**	.8954**
CExp	—	—	.2650**	.0163**	.3724**	.0468**	.3602**	.0441**	.5853**	.2055**
TechS	—	—	–.1845**	–.0279**	–.2174**	–.0288**	–.1849**	–.0351**	–.1537**	–.0975**
SocialNet	—	—	–.1758**	–.0207**	–.2451**	–.0782**	–.2140**	–.0772**	–.1976**	–.4158**
PromoD	—	—	5.2579**	—	4.6264**	—	3.9354**	—	2.2350**	—
CrossP	—	—	—	1.2462**	—	1.1310**	—	1.1246**	—	.5707**
Dist	—	—	–.0788*	–.0656	–.0334*	–.1471	–.0027*	–.1346	–.0394*	–.0385
Gender	—	—	.7644	.0218	.8504	.0524	.8482	.0456	.9690	.1114
Race	—	—	.8390	.0406	.8460	.0671	.8523	.0634	1.0673	.1102
Age	—	—	.0482	.1082	.0666	.1487	.0850	.1399	.6973	.1844
Intercept	12.7153**	2.6589**	11.7622**	2.5514**	11.2091**	2.3329**	9.5218**	1.6543**	6.6342*	1.2867*
Serial correlation	X	X	X	X	X	X	.0178*	.0491	.0076*	.0128
Cross-correlation	X		.4928*		.4726*		.4568*		.4124*	
Heterogeneity	X		✓		✓		✓		✓	
Number of observations	66,980		66,980		66,980		66,980		66,980	
Sample size	788		788		788		788		788	
LMD	–97,534.30		–92,754.71		–91,243.21		–83,385.43		–75,752.36	
Model description	Standard TE model		Model 1 + Controls		Model 2 + Interaction		Model 3 + Serial correlation		Model 4 with Tobit	

B: Customer Social Media Participation

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
PrivCon	–2.2369**	–.7076**	–.7377**	–.6685**	–.1766**
IMov	1.7925**	.4170**	.1901**	.7802**	.2865**
TechS	.8375*	.0270*	.3165*	.4064*	.0521*
SMov	.7714**	.2279**	.0167**	.4032**	.0771**
OEnt	1.0763**	.3422**	.1826**	.2069**	.0509**
TimeOnSocialNet	1.8047**	1.4342**	1.4077**	1.2919**	1.1770**
Gender	—	.0114	.0160	.0287	.0095
Race	—	–.1673	–.0253	–.3322	–.0297
Age	—	–.0029	–.0061	–.0052	–.0043
Intercept	–4.2156*	–.5074*	–1.3272*	–.3041*	–.4516*
Cross-correlation (spending, participation)	—	.2432**	.2134**	.1842**	.1426**
Cross-correlation (cross-buying, participation)	—	.0967	.0826	.0626	.0414
Heterogeneity	X	✓	✓	✓	✓
Number of observations	66,980	66,980	66,980	66,980	66,980
Sample size	788	788	788	788	788
LMD	–97,534.30	–92,754.71	–91,243.21	–83,385.43	–75,752.36

*$p \leq .05$ (parameter is significant at the 95% level; i.e., the 95% confidence interval does not contain 0).
**$p \leq .01$ (parameter is significant at the 99% level; i.e., the 99% confidence interval does not contain 0).
Notes: The sample size of 788 consumers is based on a matched pair of 394 customers from each of the treatment and control groups.

TABLE 5
Results of the DID Model: Customer Profitability and Cross-Buying Behavior

Variables	Profit	Cross-Buying
TCust	.0190	.1029
FGC	.0114	.1990*
TCust × FGC	1.1511**	.4873**
TCust × FGC × TVAd	.0034**	.0067**
TCust × FGC × Email	.0764**	.0115**
TCust × FGC × CExp	.1962**	.0507**
TCust × FGC × TechS	.6921**	.0586**
TCust × FGC × SocialNet	.7856**	.1709**
TVAd	.4310**	.2762**
Email	.6482**	.4325**
CExp	1.3341**	.2294**
TechS	−.7435**	−.4107**
SocialNet	−1.1248**	−.6669**
PromoD	−1.7639**	—
CrossP	—	.6543**
Dist	−.4610*	−.0310
Gender	.4452	.4224
Race	.9708	.2184
Age	.2844	.3019
Intercept	3.3443**	1.7202**
Serial correlation	.0089	.0321
Cross-correlation (profit, cross-buying)	.2134*	
Heterogeneity	✓	
Number of observations	140,080	
Sample size	824	
LMD	−54,233.61	

*$p \leq .05$ (parameter is significant at the 95% level; i.e., the 95% confidence interval does not contain 0).
**$p \leq .01$ (parameter is significant at the 99% level; i.e., the 99% confidence interval does not contain 0).
Notes: The sample size of 788 consumers is based on a matched pair of 394 customers from each of the treatment and control groups.

(see Table 5). We also reestimate the TE model (Equations 5–7) with customer profitability as the dependent variable. Table 6 presents the results of this estimation (note that because the results from customers' social media participation equations are similar to the previous results, we do not present them in the article; these results are available on request). The main takeaway from these additional analyses is that FGC has a positive impact on customer profitability. These results suggest that FGC may be used not only to promote products on sale but also to influence customer purchases of high-margin products, thus leading to increased customer profitability.

Robustness Checks

We perform various checks to ascertain that our core results are robust to alternative operationalization of variables, alternative model specifications, and the presence of any outliers. With respect to variable operationalization, instead of using length of tenure, we use the number of purchase occasions as a proxy for customer experience. Following Reinartz and Kumar (2003), we also examine the effect of "profitable" customer duration; we do so by weighting customer experience by the average profitability of each customer. For the operationalization of television advertising, we weight the television ad stock by customers' trust in television ads, which is measured through the customer survey (instead of the number of hours of television watched). We also use the actual length of the television advertisements. We use an alternative operationalization for the cross-category promotion variable, in which we take into account the proportion of product items bought on promotion within a category. We find the results to be robust to all these alternative variable operationalizations.

Next, we reestimate the DID model using a different post-FGC time period. In our sample, 90% of the customers in the treatment group joined the firm's social media page within one year of the firm's social media initiative (August 2009). Thus, we construct a new post-FGC time period by removing data from August 2009 through August 2010 (56 weeks) from the post-FGC period. We then reestimate the DID model with the remaining 29 weeks constituting the post-FGC period. We also estimate our TE model by selecting the control group customers randomly instead of using a matched sample. Finally, we estimate the DID and the TE models by assuming heterogeneity in all of the coefficients (as opposed to only the intercepts). We find the results to be robust to all these alternative model specifications.

We conduct the following checks to assess the sensitivity of results to the presence of potential outliers. First, we reestimate the DID and the TE models by removing customers who have very high customer spending and cross-buying (i.e., whose spending and cross-buying are two standard deviations above the respective mean values). Second, because the retailer advertises heavily on television during certain time periods (e.g., Christmas, Thanksgiving), the GRPs of TV ads are higher during these time periods. We plot the GRPs of TV ads across the study time period and identify periods in which these values are higher than normal. We then remove data from these time periods and reestimate the DID and the TE models. We find the results to be robust to the exclusion of outliers. Details and results of all these alternative models are available from the authors on request.

Finally, we use empirical tests to ensure that our exclusion restrictions (related to the joint models presented in Equations 1–2 and Equations 5–7) are valid. We follow Wooldridge (2010) and regress the error terms of an equation on the excluded variable to find the significance of the parameter associated with the relevant excluded variable. Wooldridge suggests that the restrictions criterion is met if the parameter corresponding to the excluded variable is insignificant. We describe the method in detail in Web Appendix W10. We find that the criterion for the exclusion restrictions is met in our empirical context.

Discussion

Summary of Findings and Theoretical Implications

According to a recent survey of chief marketing officers (CMOs; Moorman 2015), social media spending as a percentage

TABLE 6
Results of the TE Model: Customer Profitability and Cross-Buying Behavior

Variables	Profit	Cross-Buying
FGC	.0808**	.0826**
FGC × TVAd	.0011**	3.E-05**
FGC × Email	.0294**	.0853**
FGC × CExp	.0114**	.0756**
FGC × TechS	.0581**	.0189**
FGC × SocialNet	.0541**	.0376**
TVAd	.0157**	.0089**
Email	.1546**	.1084**
CExp	.0392**	.3093**
TechS	–.9235**	–.0356**
SocialNet	–.1407**	–.0822**
PromoD	–2.7377**	—
CrossP	—	.9564**
Dist	–.0834*	–.0004
Gender	1.2483	.0753
Race	1.1031	.0473
Age	.0589	.0059
Intercept	3.7150**	1.0353*
Serial correlation	.0038*	.0087
Cross-correlation (profit, cross-buying)	.3164*	
Heterogeneity	✓	
Number of observations	66,980	
Sample	788	
LMD	–80,741.24	

*$p \leq .05$ (parameter is significant at the 95% level; i.e., the 95% confidence interval does not contain 0).
**$p \leq .01$ (parameter is significant at the 99% level; i.e., the 99% confidence interval does not contain 0).
Notes: The sample size of 788 consumers is based on a matched pair of 394 customers from each of the treatment and control groups.

of marketing spending is expected to more than double in the next five years. However, only 13.2% of executives surveyed report that they have been able to measure the impact of social media spending. Using actual in-store purchase data, we find that FGC can not only enhance the transaction and relationship sides of customer–firm interactions (measured by spending and cross-buying, respectively) but also play a role in increasing customer profitability. In addition, we find that FGC works synergistically with television- and e-mail-based marketing communication. Our results suggest that FGC has a greater effect on customers with a longer customer–firm relationship, who are technologically savvy, and who are more prone to social networking.

From a theoretical contribution perspective, although many extant studies in the area of social media have shed light on the impact of UGC on market outcomes, the effect of FGC on customer behavior has received less attention. Our study contributes to the social media literature by demonstrating the impact of FGC on three key customer metrics: spending, cross-buying, and profitability. It is critical to note that we do so after ruling out customer self-selection, a thorny issue in the context of customers' social media participation. Our study also contributes to the literature on IMC and multichannel marketing, which has called for researchers to facilitate a better understanding of synergies across multiple media to build brand equity (Joo et al. 2014; Lin, Venkataraman, and Jap 2013; Naik and Raman 2003). By studying the synergistic effects of FGC on customers' in-store (offline) purchase behavior, we establish not only the synergy effect across different media (social media, television, and e-mail marketing communication) but also cross-channel (online–offline) synergy effects. This has implications for optimal resource allocation across media as well as cross-channel coordination of firms' communication strategies. Our utilization of a richer specification for FGC that captures valence, receptivity, and susceptibility also helps provide a deeper understanding of the theoretical underpinnings of the FGC effect. We demonstrate that the effect of FGC receptivity is the greatest (vs. the effects of valence and susceptibility), which suggests that it is social media's ability to give "voice" to customers in the form of likes and comments that makes FGC more effective.

Managerial Implications

The results from our study provide several managerial implications. We offer the following prescriptions for managers.

Embrace social media. The clear messages from our study are that social media marketing matters and that managers should embrace it to communicate and nurture relationships with customers. We find that investing in developing a social media community with a dedicated fan base (e.g., a Facebook page) can significantly strengthen customer–firm relationships and can lead to a definitive impact on the firm's revenues and profits. In our study, we note that 4.95% of our focal firm's total customer base elects to receive FGC. Although this level of participation is fairly consistent with social media participation rates for other brands and retailers,[11] we believe that as more of a firm's clientele participates in a firm's social media page, the resulting benefits for the firm (in terms of customer spending, cross-buying, and profitability) can be greater. However, firms also need to take into consideration the costs of assembling and constantly updating FGC. Given that television advertising is measured in GRPs, it is difficult for us to compare the effects of FGC and television advertising; nevertheless, to quantify the impact of FGC on customer behavior, we conduct an exercise that is akin to elasticity analysis. We report the results in Table 7 (for more details related to this analysis, see Web Appendix

[11]To determine how our focal firm's customer participation rate of 4.95% compares with other brands and retailers, we collected information on the number of people who "liked" the Facebook pages of some well-known brands (e.g., Tide, Campbell's Condensed Soup, Honda CRV, Organic Valley, Cheerios) and retailers (e.g., Stop & Shop, Kroger, ShopRite, Safeway, H-E-B) and performed an additional analysis. We find that the percentage of the customer base that participates in these firms' social media sites ranges from 1.00% to 7.35%, with an average of 3.70%. Thus, we believe that the customer participation rate for our focal retailer is consistent with current industry trends. More details are available from the authors on request.

TABLE 7
Elasticity Analysis: Social, Traditional, and Digital Media

Type of Marketing Communication (Variable)	Overall		First Six Months		Last Six Months	
	Spending	Cross-Buying	Spending	Cross-Buying	Spending	Cross-Buying
Social media (FGC)	.0140 (.0027)	.0587 (.0035)	.0060 (.0007)	.0441 (.0061)	.0108 (.0023)	.0493 (.0049)
Digital media (Email)	.0913 (.0215)	.0433 (.0165)	.0799 (.0137)	.0409 (.0043)	.0888 (.0358)	.0408 (.0202)
Traditional media (TVAd)	.1010 (.0075)	.0507 (.0038)	.0949 (.0023)	.0457 (.0202)	.0968 (.0097)	.0532 (.0085)

Notes: The elasticity calculations are based on the results of the TE model. "First Six Months" refers to the period from August 2009 to January 2010 (the first six months since inception of the firm's social media page). "Last Six Months" refers to the period from October 2010 to March 2011 (the last six months of our data's post-FGC period). Standard errors are shown in parentheses.

W11). We find that the elasticity of FGC with respect to customer spending is .014, which is lower than the elasticities of television advertising and e-mail messages (.101 and .091, respectively). However, we find that the elasticity of FGC (.059) is greater than that of television advertising and e-mail messages (.051 and .043, respectively) for customer cross-buying. This suggests that FGC can play a key role in strengthening customers' relationship with the firm by encouraging them to buy across several product categories.

To further understand whether the positive effect of FGC is simply due to its attractiveness as a new form of marketing communication or whether the effect is a long-lasting one, we split the post-FGC period into two six-month time periods. In Table 7, we note that the elasticities of FGC in the last six months (in the post-FGC period) for customer spending and cross-buying are actually greater than the corresponding elasticities from the first six months of the post-FGC time period. These findings suggest that the FGC effect is persistent in the post-FGC time period and that its impact is not purely attributable to the novelty of the launch of the social media page by the focal firm. Thus, while we still find traditional media advertising to be more effective in our context, we believe that FGC, though a nascent channel in our study, also yields sustained results for the firm.

Exploit synergies across media. Our study suggests a synergistic relationship between social media and other media used for marketing communication: television and e-mails. As social media gains importance and becomes the proverbial "talk of the town," managers must take care to not abandon traditional or other forms of advertising, because these have substantial synergies between them. To illustrate these synergistic effects, we performed an additional analysis (see Table 8). We find that the percentage increases in customer spending and cross-buying that result from the synergistic effect of FGC and television advertising are quite substantial (1.03% and .84% for customer spending and cross-buying, respectively). The percentage increases in customer spending and cross-buying that result from the synergistic effect between FGC and e-mails are 2.02% and 1.22%, respectively. These results highlight the need to integrate marketing communication across different media and to help allay managers' concerns regarding measurable returns to social media marketing. We encourage social media managers to perform simulation exercises to determine optimal allocation of resources across different media.

Monitor FGC popularity. The return on investment in social CRM is determined not only by a firm's investment in social media but also by consumers' level of engagement with the firm's social media page (Hoffman and Fodor 2010). In our study, we incorporate a rich measure of FGC that comprises the sentiment (or valence) of posts, popularity (or receptivity) of posts, and customer susceptibility to social media posts. Whereas FGC valence captures a firm's effort in

TABLE 8
Synergistic Effects of FGC with Television Advertising and E-Mail Marketing

Simulation	Variables in the Model	% Change in Spending	% Change in Cross-Buying
Traditional ad (TVAd) and FGC	Main effects of FGC and TVAd	2.08 (.23)	1.06 (.14)
	Main effects of FGC and TVAd and interaction effect between FGC and TVAd	3.11 (1.33)	1.90 (.85)
	Incremental change	1.03	.84
Digital ad (Email) and FGC	Main effect of FGC and Email	3.25 (.54)	1.54 (.35)
	Main effects of FGC and Email and interaction effect between FGC and Email	5.27 (.68)	2.76 (1.18)
	Incremental change	2.02	1.22

Notes: The base case is the TE model with the main effect of FGC but without TVAd and Email. All the models include the control variables that we presented in Equations 5–7. Standard errors are shown in parentheses.

creating meaningful content that facilitates more positive customer–firm interactions, receptivity and susceptibility capture the extent to which customers' interest is piqued by FGC and their predisposition to using social media. Although our FGC measure (presented in Equation 8) is a composite measure, from a managerial perspective, it may be more useful to assess the differential effects of these three dimensions. Therefore, we compute the elasticities of these three dimensions with respect to customer spending and cross-buying behavior (more details on the analysis appear in Web Appendix W12). We present the results of this elasticity analysis in Table 9.

Our results suggest that FGC receptivity has the greatest impact, followed by FGC valence and susceptibility. From Table 9, we note that the elasticity of FGC receptivity with respect to customer spending and cross-buying is .019 and .086, respectively. The next most effective FGC component is valence, with elasticity values of .013 and .029 for customer spending and cross-buying, respectively. Although we find that customer susceptibility also affects customer behavior, the elasticity of this particular FGC component is the lowest among the three components. Because FGC receptivity involves direct customer involvement, we believe our results make a strong case for firms to grow their "fan" base, monitor the level of customer engagement, and post measures of popularity on their brand social media pages.

In addition to providing more general prescriptions for marketing managers, we also conducted a more context-specific post hoc analysis by identifying the alcoholic products for which FGC was most effective. We worked with the treatment group consumers and simulated their shopping baskets in response to an increase in FGC level (the details of the simulation appear in Web Appendix W13). We find that the shopping baskets of this set of consumers consisted mostly of products in the red, white, and sparkling wine categories. The buying behavior for wines is a complex one given that consumers have to take into consideration several attributes, such as varietal, label (region of origin), ratings (e.g., a Parker's rating), sweetness, acidity, tannin, fruit, and body (Sáenz-Navajas et al. 2013). Therefore, to make more informed decisions with respect to wine purchases, consumers may seek more information about these attributes. We believe that this is a case in which social media communications can increase customer access to more nuanced product-related information. We note that in our context, wine products are also generally higher-margin products (on average, their margin is 30% higher than other alcoholic beverage products). The takeaway is that FGC is able to drive sales toward higher-margin categories in our study.

Utilize social media for strengthening brand connections. In line with our findings that FGC has a greater impact on customers who have longer tenure with a firm and on customers who are tech savvy and active on social media, we suggest that special product-focused "interaction forums" could be created for such customers. By administering surveys, a firm can identify tech-savvy and social network–prone customers and encourage them to join the firm's social media page. We suggest that developing brand communities that consist of loyal, tech-savvy, and social media–savvy customers will aid firms' long-term financial interests.

TABLE 9
Elasticity Analysis: Effect of the Three Dimensions of FGC on Customer Behavior

Focal Dimension of FGC	Spending	Cross-Buying
Valence	.0128 (.0068)	.0285 (.0061)
Receptivity	.0188 (.0020)	.0864 (.0162)
Susceptibility	.0092 (.0032)	.0076 (.0028)

Notes: The elasticity calculations are based on the results of the TE model. Standard errors are shown in parentheses.

Conclusion and Limitations

Although our study offers key insights into FGC's impact and contributes to both theory and practice, it has several limitations. While we leverage a unique data set that is built on customer social media participation and transaction data, we acknowledge that we analyze only one type of social media. Further research can explore the role of other kinds of social media, such as blogs or tweets. Because of the lack of data, we did not consider the behavior of the same set of customers across different types of social media (e.g., both Facebook and Twitter), and this could be an avenue for further research. We considered sales at the focal retailer's physical store because this channel constitutes the majority of the sales. Other research could examine online channel sales in addition to sales at brick-and-mortar stores. This study is in the context of experience goods; extensions to other contexts (e.g., search goods, consumer packaged goods) could lend generalizability to our results. Future researchers could also conduct a detailed message-level analysis that examines the type of messages (e.g., informative vs. persuasive) and also includes a supply-side analysis of FGC. We note that not all the customers who participate in social media will intently read FGC. As is typical of research in the social media domain that uses observational data, we are unable to parse this issue. Furthermore, we analyze the impact of FGC at a point in time when the potential customer base that opts to receive FGC is of a moderate size; it may be worthwhile for future studies to revisit this issue when the FGC participation rates are high. We realize that some of the study's limitations are due to lack of relevant data sets (e.g., not having television advertising data at the individual customer level) and hope that as more data become available, further research can build on our study to explore other issues related to FGC in social media.

Appendix: Examples of FGC

The focal retailer uses FGC to communicate several types of information such as information about specific products, events in physical stores, and specific wines in stock, along with images and links to relevant content. Messages posted on social media may convey information about special events such as wine tastings, new wine/liquor arrivals, and inventory information. Sometimes the postings may also relate to local events (e.g., art shows). Thus, the focal firm's postings on the social media platform constitute both promotional and nonpromotional messages. We present some examples of FGC from the retailer' social media page. Note that the postings are usually accompanied by relevant visuals such as photos and videos.

- Join Kate in our Reserve Room today as we pour wines from famous producers, such as Schloss Vollrads, Banfi and Fonseca. Join us 4:00–7:00pm!
- Plenty of wines will be open at the store this weekend, including these staff favorites! Join us Friday and Saturday 12:00–6:00pm.
- There are more amazing wines open at our tasting center than we can even fit in this status update... get to the store before 6pm and get your sample on!
- Our class tonight is nearly full but there are a few spots left in our Friday class –an evening with Hermann J. Wiemer estate manager Oskar Bynke.
- FYI: We're open Monday 9:30–5:00 for any Labor Day needs!
- FREE Jim Beam White Label & Red Stag samples on Saturday July 10th from 12–3pm.

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